Research Synopsis

on

Some Studies on Automatic Liver Segmentation

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Contents

1. Introduction 3
1.1 Liver Cancer Statistics 4
1.2 Liver Anatomy 5
1.3 Functions of the liver 6
1.4 Types and Stages of liver cancer 7
Stage I (stage 1 liver cancer) 7
Stage II (stage 2 liver cancer) 7
Stage III (stage 3 liver cancer) 7
Stage IIIA 7
Stage IIIB 7
Stage IIIC 7
Stage IV (stage 4 liver cancer) 7
2. Literature Review 8
2.1 Algorithms for Liver Segmentation 8
2.1.1 Methods based on spatial and geometric prior knowledge 8
2.1.2 Methods based local image features and spacial context 9
2.1.3 Methods based on local image features with voxel-wise classification 9
2.1.4 Semi-automated methods 9
2.1.5 Methods based on neural networks and deep learning 10
2.2 Algorithms for Liver Tumor Segmentation 10
2.2.1 Thresholding methods 10
2.2.3 Spatial regularization methods 11
2.2.4 Local image features with supervised classification and unsupervised clustering methods 11
2.2.5 Semi-automated methods 11
2.2.6 Deep Learning methods 11
3. Problem Definition 12
4. Objectives 13
5. Methodology 13
6. Importance of study/ Society application 14
6.1 International Status 14
6.2 National Status 15
6.3 Significance of the study 15

7. Proposed work Plan 16
8. References 16

Some Studies on Automatic Liver Segmentation

1. Introduction

The healthcare sector is on the high priority sector and people expect the highest level of care and services. Nowadays mostly the interpretations of medical data are being done by a medical expert using different medical imaging modalities. Medical imaging is an important tool for diagnosis and treatment planning [4].

The liver plays a very vital role in the detoxification of the human body. Due to its detoxification function, the liver is one of the essential organs in the human body. Radiologists and oncologists analyze computed tomography (CT) or magnetic resonance images (MRI) to study livers' anomalies in shape and texture. These anomalies are important biomarkers for initial disease diagnosis and progression in both primary and secondary hepatic tumor disease [11].

Liver and liver tumor segmentation is a prerequisite for many clinical applications such as computer-assisted detection/diagnosis (CAD), liver surgery planning, treatment planning, and post-treatment evaluation. Apart from liver surgery planning, high accuracy for liver and liver tumor volume determination is also essential for Selective Internal Radiation Therapy (SIRT) planning and reducing the risk of excess or insufficient radiation dose as a patient's liver volume determines the amount of radiation to be delivered. Manual delineation of these tumors is time-consuming and the segmentation is reliant on the operator, for these reasons automatic segmentation of liver and liver tumors has been of interest to many researchers [9]. Because of that Liver Segmentation is a task of great clinical interest since it allows physicians benefiting from reproducible and reliable methods for segmenting affected lesions. Accurate segmentation would indeed help them during the evaluation of the lesions, the choice of treatment and treatment planning. Medical imaging is a specific field of Computer Vision that deals with medical images. During the last decades, many tools have been developed for the imaging of the body, first producing 2D representations of the body (X-Ray, Ultra-Sound) and more recently 3D volumes a set of 2D images of the body. These imaging modalities, such as Computed Tomography (CT) or Magnetic Resonance Imaging (MRI), allow taking 3D images of the body in a non-invasive way. Thus, medical images became increasingly important for medical practice. These images indeed contribute too many medical tasks such as diagnosis, follow-up of patients and evaluation of treatments [28]. The image modalities will help the medical experts to diagnose liver cancer and to decide its different stages. Mostly the interpretations of medical data are being done by a medical expert. In terms of image interpretation by a human expert, it is quite limited due to its subjectivity, complexity of the image; extensive variations exist across different

interpreters, and fatigue. An alternative solution is using Automatic computer-aided diagnosis (CAD) techniques using advanced image processing tools and Algorithms [4].

Despite lots of attention, fully automatic liver and liver tumor segmentation remain a challenging task, fig.1 shows that the sample CT slices with difficulties in liver segmentation mainly because of the variability of the liver and tumor shapes and the intensity patterns inside and in the neighborhood of them. Being a soft organ, the liver shape is highly dependent on adjacent organs within the abdomen. Moreover, many pathologies can have a strong effect on the appearance and the shape of the liver while most of the time clearly defined edges are not visible on many sides of the liver. In particular, the intensity differences between the liver and the heart or the spleen or the stomach are very small [9]. The intensity in nearby organs, tissue linkage, low contrast, and overlapping of different organs are major challenging problems [6].

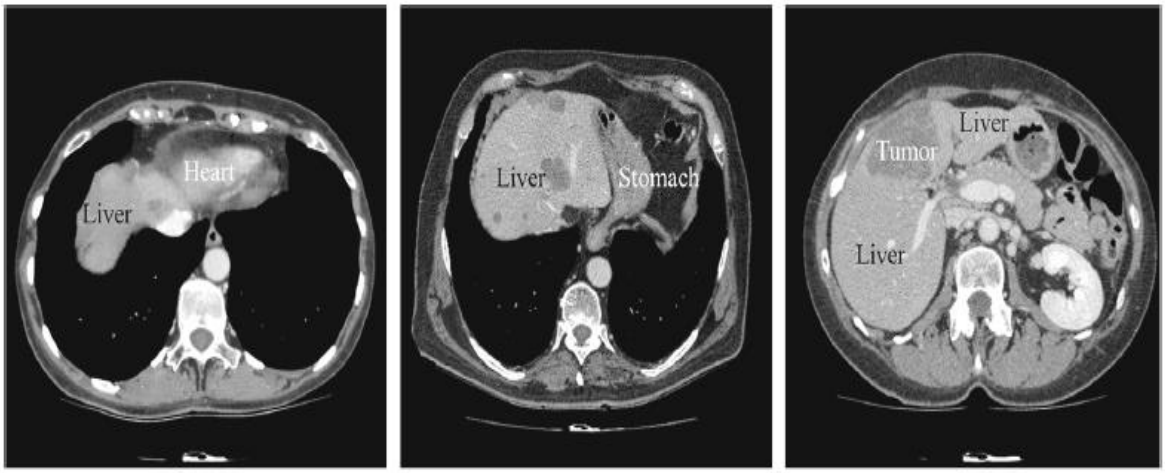

Fig.1 Examples of difficulties of liver segmentation: sample CT slices with ambiguous boundary between liver and heart, stomach and tumor [9]

1.1 Liver Cancer Statistics

According to estimates from the World Health Organization (WHO) in 2015, cancer is the first or second leading cause of death before age 70 years in 91 of 172 countries. The status report on the global burden of cancer worldwide using the GLOBOCAN 2018 estimates of cancer incidence and mortality produced by the International Agency for Research on Cancer, with a focus on geographic variability across 20 world regions. There will be an estimated 18.1 million new cancer cases (17.0 million excluding nonmelanoma skin cancer) in which 4.7% is the liver cancer diagnosed and 9.6 million cancer deaths (9.5 million excluding nonmelanoma skin cancer) in 2018 in which 8.2% deaths due to liver cancer [1]. The GLOBOCAN 2018 status report of cancer estimates in India is 1157294 and out of which 2.4% (27670) is liver cancer cases and 3.3% (25627) is the mortality rate. It is eighth-most cancer cause deaths in India [25]. Cancers are the main cause of mortality and health problem worldwide, and liver cancer is one of the most common. It is considered as the sixth most common cancer and the second leading cause of cancer deaths around the world. The increasing mortality rate of liver cancer there is an urgent need to diagnose liver cancer at an

early stage to provide the right treatment by clinicians and increase the survival rate of the patient [2].

1.2 Liver Anatomy

The liver is located in the upper right-hand portion of the abdominal cavity, beneath the diaphragm, and on top of the stomach, right kidney, and intestines as shown in fig. 2.

Shaped like a cone, the liver is a dark reddish-brown organ that weighs approximately 1.5 Kg and has a width of about 15 cm. It is the heaviest internal organ and the largest gland in the human body as shown in fig. 3.

Two distinct sources supply blood to the liver, including the following:

- Oxygenated blood flows in from the hepatic artery
- Nutrient-rich blood flows in from the hepatic portal vein

The liver holds about 13% of the body's blood supply at any given moment. The liver consists of 2 main lobes. Both are made up of 8 segments that consist of 1,000 lobules (small lobes). These lobules are connected to small ducts (tubes) that connect with larger ducts to form the common hepatic duct. The common hepatic duct transports the bile made by the liver cells to the gallbladder and duodenum (the first part of the small intestine) via the common bile duct [26].

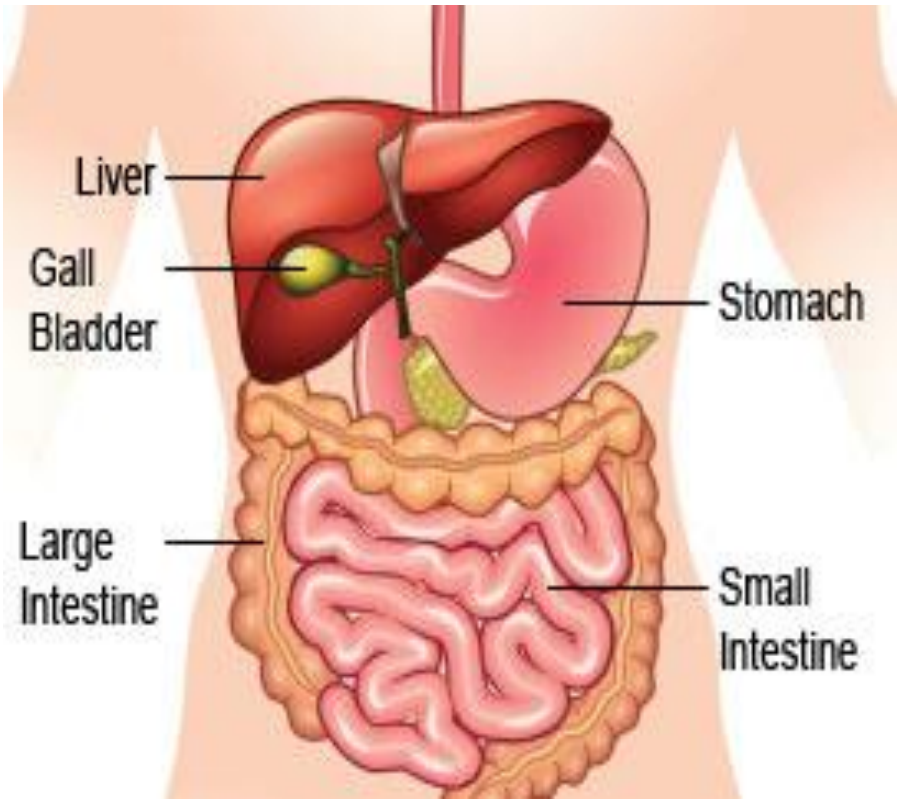

Fig.2 Liver Shape and Position in Human Body

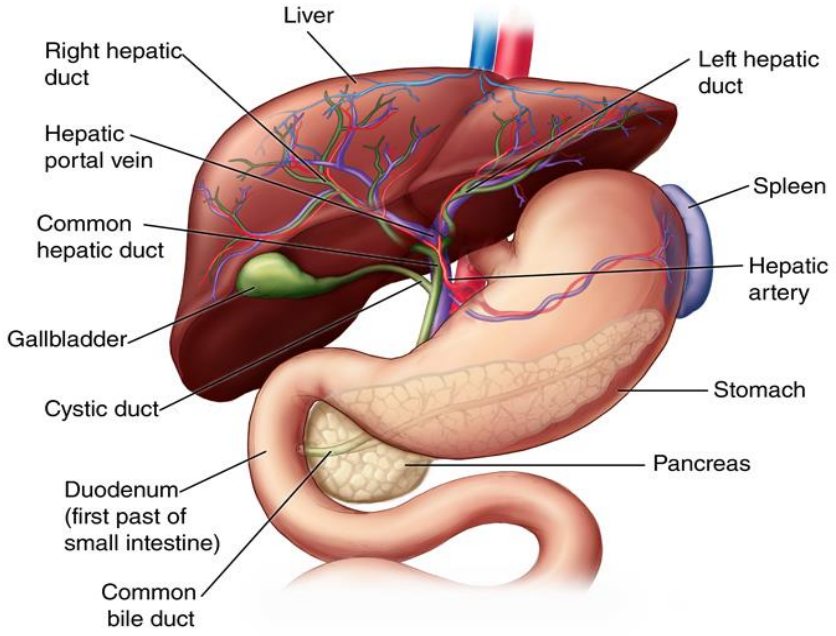

Fig.3 Liver Anatomy

1.3 Functions of the liver

The liver regulates most chemical levels in the blood and excretes a product called bile. This helps carry away waste products from the liver. All the blood leaving the stomach and intestines passes through the liver. The liver processes this blood and breaks down balances, and creates the nutrients and also metabolizes drugs into forms that are easier to use for the rest of the body or that are nontoxic. More than 500 vital functions have been identified with the liver. Some of the more well-known functions include the following: [26]

- Production of bile, which helps carry away waste and break down fats in the small intestine during digestion
- Production of certain proteins for blood plasma
- Production of cholesterol and special proteins to help carry fats through the body
- Conversion of excess glucose into glycogen for storage (glycogen can later be converted back to glucose for energy) and to balance and make glucose as needed
- Regulation of blood levels of amino acids, which form the building blocks of proteins
- Processing of haemoglobin for use of its iron content (the liver stores iron)
- Conversion of poisonous ammonia to urea (urea is an end product of protein metabolism and is excreted in the urine)
- Clearing the blood of drugs and other poisonous substances
- Regulating blood clotting
- Resisting infections by making immune factors and removing bacteria from the bloodstream
- Clearance of bilirubin, also from red blood cells. If there is an accumulation of bilirubin, the skin and eyes turn yellow.

- When the liver has broken down harmful substances, its by-products are excreted into the bile or blood. Bile by-products enter the intestine and leave the body in the form of feces. Blood by-products are filtered out by the kidneys, and leave the body in the form of urine.

1.4 Types and Stages of liver cancer

Liver cancer is divided into two types: primary and secondary Liver Cancer. The primary Liver Cancer starts in the liver, but the secondary Liver Cancer begins in other organs of the body and spreads to the liver due to metastases of this cancer and creation of the most common cases including colorectal, breast, pancreatic, ovarian and lung cancers. Primary liver tumors include Hepatocellular carcinoma, Cholangio carcinoma, and Sarcoma which account for about 6% of the total cancer burden worldwide [3].

The liver cancer is divided into four different stages as shown in fig.4, liver treatment decision begins with determining the stage, or progression, of the disease. The stage of liver cancer is one of the most important factors in evaluating treatment options [27].

Stage I (stage 1 liver cancer)
The single primary tumor (any size) has not grown into any blood vessels. Cancer has not spread to nearby lymph nodes or distant sites.

Stage II (stage 2 liver cancer)
A single primary tumor (any size) has grown into the blood vessels, or several small tumors are present, all less than five centimeters (two inches) in diameter. Cancer has not spread to nearby lymph nodes or distant sites.

Stage III (stage 3 liver cancer)
This stage has three subcategories:

Stage IIIA
Several tumors have been found, and at least one is larger than five centimeters. Cancer has not spread to nearby lymph nodes or distant sites.

Stage IIIB
Several tumors have been found, and at least one tumor is growing into a branch of the portal vein or the hepatic vein. Liver cancer has not spread to nearby lymph nodes or distant sites.

Stage IIIC
The tumor has grown into a nearby organ (other than the gallbladder), or the tumor has grown into the outer covering of the liver. Cancer has not spread to nearby lymph nodes or distant sites.

Stage IV (stage 4 liver cancer)
Cancer has spread to nearby lymph nodes and may have grown into nearby blood vessels or organs. Advanced liver cancer does not often metastasize (or travel to distant organs), but when it does, it is most likely to spread to the lungs and bones.

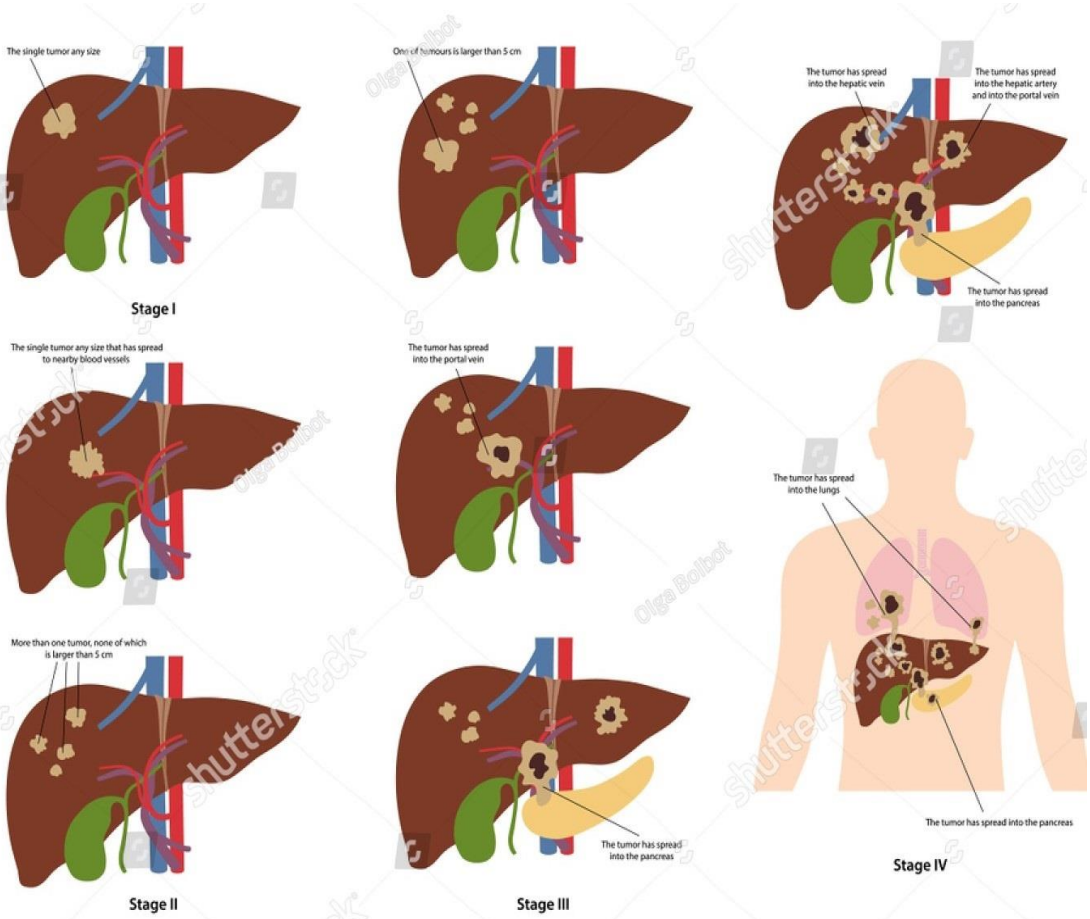
The single tumor any size
Stage I
The single tumor any size that has spread to nearby blood vessels
More than one tumor, none of which is larger than 5 cm
Stage II
The tumor has spread into the portal vein
The tumor has spread into the pancreas
Stage III
The tumor has spread into the hepatic vein
The tumor has spread into the hepatic artery and into the portal vein
The tumor has spread into the pancreas
The tumor has spread into the lungs
The tumor has spread into the pancreas
Stage IV

Fig.4 Liver Cancer Stages

2. Literature Review

The task of liver and liver tumor segmentation identifies a set of voxels that describes the region of the liver in a medical image. In the past, many researchers have proposed a variety of methods for liver segmentation and tumor Segmentation. Overview of the methods is as follows – [7] [8] [9] [10] [11]

2.1 Algorithms for Liver Segmentation

The liver segmentation algorithms published have been categorized into four different categories as follows -

2.1.1 Methods based on spatial and geometric prior knowledge

Shape/Structure-based Model use statistical Shape Model (SSM) followed by a deformable model performing free form deformation had become a valuable method for liver segmentation. In the SSM approach, create a Probabilistic model as prior knowledge for liver shape. Moreover, variations and further enhancement of SSM such as 3D-SSM based on an intensity profiled appearance model, incorporating non-rigid template matching, initialization

of SSMs utilizing an evolutionary algorithm, hierarchical SSMs, and deformable SSM used for automatic liver segmentation.

2.1.2 Methods based local image features and spacial context

Probabilistic atlas (PA) utilizes both the prior shape and the spatial location information to achieve a refined segmentation. It is a specific model for a population of images with parameters that are learned from a training dataset. It can incorporate relations between adjacent abdominal structures to define an anatomical structure surrounding the liver. The multi-atlas method improves the performance of segmentation using the non-rigid registration with a B-spline transformation model that uses local features.

Gray level methods utilize statistics to estimate the intensity distribution of the liver. The combination of PA and SSM has shown the improvement in accuracy of segmentation. Gray level methods utilize statistics to estimate the intensity distribution of the liver.

Methods to segment the liver using morphological filters and intensity distributions and pattern features. Graph Cut (GC) methods segment the image into background and liver. All pixels respectively voxels of the image is represented by a set of vertices. Combined a statistical atlas-based shape estimation with a graph cuts algorithm to incorporate constraints from the estimated shape and a neighboring structure.

2.1.3 Methods based on local image features with voxel-wise classification

Classification methods which concentrate on liver and tumors segmentation. Existing, approaches combine AdaBoost classifier to identify location or Liver boundaries and free-form deformation for segmentation refinement. Feature-based classification combine AdaBoost with random walk algorithms that produce comparable results with previous methods.

Combining a simultaneous liver detection and probabilistic segmentation using 3D CNN with accuracy refinement of the segmentation afterward using graph cut, 3D CNN in combination with random fields, 3D CNN following a surface evolution algorithm. Moreover, a 3D CNN is has been proposed to learn a subject-specific probability map of the liver. Afterward global and local appearance information is incorporated into a segmentation model which is globally optimized for surface evolution.

2.1.4 Semi-automated methods

Automated segmentation methods require a large dataset for modeling the different variations of livers. Semi-automatic methods were generally regarded as more robust especially in the case of irregular livers. However, segmentation results of semi-automatic methods are reliant on the operator skill and can differ. Semi-automated methods differ in their required degree of manual input. Popular methods such as region growing generally require often costly pre- and post-processing in form of manual seed region initialization and segmentation refinement. Graph cut (GC) segmentation methods are in consequence of its semi-automatic ability to edit segmentation results interactively, suitable for clinical applications. The 2D to 3D interpolation methods based on shape models to reconstruct the whole 3D surface based

on selected 2D contours, and slice-based segmentation using distance transformations. 3D segmentation using a combination of k-means clustering and region growing followed by a contouring algorithm for refined segmentation which is based on a manually selected single slice.

2.1.5 Methods based on neural networks and deep learning

The Neural network-based approach has heavily relied on pre- and post-processing to discard irrelevant regions upfront and ensure smooth boundaries by morphological operations and b-spline smoothing afterward. Modern Convolutional Neural Networks is a data-driven algorithm which can be optimized end-to-end without hand-craft feature engineering. Today convolutional neural networks are widely used in automatic semantic segmentation tasks in medical imaging without reliance on hand-crafted features.

The U-Net architecture is widely used in DCNN for biomedical image segmentation and has already proven its efficiency and robustness in several segmentation tasks. The architectural novelty in U-net over traditional semantic segmentation networks is the combination of an equal amount of upsampling and downsampling layers and the skip connections between its opposing convolution and deconvolution layers.

Wang, Chi, et al. [14] present a multi-plane network (MPNet) for the liver segmentation task with multiplane receptive field improved the performance of segmentation. Ahmad, Mubashir, et al. [6] proposed method was based on training by a Deep Belief Network for unsupervised pre-training and supervised fine-tuning. Instead of the pixel by pixel learning, they used blocks as a basic unit for feature learning to identify the liver, which saves memory and computational time. An automatic active contour method is applied to refine the liver in post-processing.

2.2 Algorithms for Liver Tumor Segmentation

Compared to liver tumor appearances differ in shape, size, and contrast. In comparison to a segment, only one region of interest, liver tumors can materialize in different numbers of occurrences often with no visible edges. Often contrast agents introduce additional noise in images. Therefore liver tumor segmentation is considered to be the more challenging task. Published methods of liver tumor segmentation can be categorized as follows -

2.2.1 Thresholding methods

Based on the assumption that gray levels of tumor areas differ from pixels belonging to regions outside the tumor, thresholding is a simple but effective tool to automatically separate tumor from liver and background. Since then thresholding based methods have set an adequate threshold value by histogram analysis, maximizing the variance between classes and iterative setting the threshold value by an isodata algorithm to improve tumor segmentation results.

2.2.3 Spatial regularization methods

Spatial regulation techniques rely on prior information about the image or morphologies e.g. size, shape, surface or spatial information of tumors. This knowledge is used to introduce constraints in the form of regularization or penalization. Adaptive thresholding methods can be combined with model-based morphological processing for heterogeneous lesion segmentation. Active contour-based tumor segmentation relies on shape and surface information and utilizes probabilistic models or histogram analysis to create segmentation maps automatically. Level set methods allow numerical computations of tumor shapes without parameterization.

2.2.4 Local image features with supervised classification and unsupervised clustering methods

The unsupervised Clustering methods include k-means and fuzzy c-means clustering with segmentation refinement using deformable models. Among supervised classification methods are, a fuzzy classification based level set approach, Support Vector Machines (SVM) in combination with a texture-based deformable surface model for segmentation refinement. AdaBoost trained on texture features and image intensity profiles, logistic regression and Random Forests (RF) recursively classifying and decomposing super voxels for improving the segmentation of tumor.

2.2.5 Semi-automated methods

Liver tumor tissues appear in different shapes, sizes, textures, contrast, and number. Therefore various semi-automatic approaches mostly combining several methods. The graph cut followed by watershed for refined segmentation results. Adaptive multi-thresholding based on cross-entropy with level set techniques for segmentation. Bayesian classification with active contours refinement relying on manually selected seeds. Support Vector Machine (SVM) for iterative 2D slice-per-slice pixel classification with morphological operations on manually selected tumor regions. SVM trained on user-selected seeds for tumor extraction with corresponding feature vector based upon small regions produced by watershed transformations, fuzzy c-means clustering on manually selected slices with segmentation refinement using hidden Markov measure field models.

2.2.6 Deep Learning methods

Deep learning methods are showing the great result in Segmentation of liver tumor. An approach introduced an 11-layer 3D CNN for segmentation and graph cut for segmentation accuracy refinement. A dense 3D conditional random field for segmentation refinement after cascading 3D CNNs (U-Net) for liver and tumor segmentation.

Trivizakis, Eleftherios, et al. [12] proposed 3D CNN takes advantage of the inter-slice tumor relationships resulting in a richer representation which gradually captures the inner and overall structure of each tumor type. 3D strided CNN successfully applied for cancer differentiation based on the raw tomographic data without pre-processing including segmentation, detection or cropping of the regions of interest.

Li, Xiaomeng, et al. [13] employed the cascaded learning strategy to reduce the overall computation time, used simple ResNet architecture is trained to get a quick but coarse segmentation of the liver.

Jiang, Huiyan, et al. [15] design an Attention Hybrid Connection Network architecture which combines soft and hard attention mechanisms and long and short skip connections. Also, a cascade network based on the liver localization network, liver segmentation network, and tumor segmentation network proposed to achieve faster network convergence and accurate semantic segmentation. The architecture combines the soft and hard attention mechanism and the short and long skip connections to achieve efficient feature extraction and fusion, and the network architecture is essentially general, can be easily extended to other applications.

Gruber, Nadja, et al. [16] used a network architecture that consists of two consecutive fully convolutional neural networks (U-Net). The first network segments the liver whereas the second network segments the actual tumor inside the liver. The joint approach could reduce the time required for computation and improve performances.

Hoogi, Assaf, et al. [17] used Active Contour for lesion segmentation using deep learning based CNN architecture with variable parameters that give better segmentation on variable lession. Gibson, Eli, et al. [18] deep-learning-based DenseVNet can segment the pancreas, esophagus, stomach, liver, spleen, gallbladder, left kidney and duodenum more accurately than previous methods using deep learning or multi-atlas label fusion.

Delmoral, Jessica C., et al. [23] the effects of Dilated Convolutional Networks are proposed, to improve the segmentation of liver tissues in CT. The introduction of a dilation module allowed the concatenation of feature maps with richer contextual information. The segmentation is implemented FCN based on the well-known U-net architecture.

Jin, Xinyu, et al. [24] fully connected U-Net with the deeper bottleneck architectures (DBA) for Liver segmentation and solve the drawbacks of the excessive amount of parameters and the insufficient depth of the network.

3. Problem Definition

From the literature, it is clear that liver cancer became the sixth most common cancer and the second leading cause of cancer deaths around the world and it is growing day by day worldwide. The statistics declared by the WHO is alarming situation worldwide. So it is very essential to address this issue on very high priority to diagnose the liver cancer at an early stage so that oncologist can properly plan the treatment.

In the medical sciences, the liver cancer is diagnosed by clinical experts/ Radiologist with the help of medical imaging scan (CT, MRI, and Ultrasound) by detecting the tumor manually with his expertise and domain knowledge. The manual procedure is time-consuming and the opinion will change person to person. Secondly, the medical imaging data is increasing day by day so it is becoming difficult to detect the cancerous cell and find out the exact volume, Location and size manually by the radiologist.

The methods proposed in the literature by the different researchers to segment liver and tumor are not self-sufficient to segment the liver and tumor with clinically considerable accuracy with no error in the segmentation. However, Liver and tumor segmentation is still a very challenging problem for the research community due to the complex background, fuzzy boundary, variability in the liver shape, the similar intensity in nearby organs, tissue linkage, low contrast, and overlapping of different organs.

Therefore there is a scope for the research on the study of liver and liver tumor segmentation and to devise the methods to provide the best suitable and robust engineering solution on the issues in liver and liver tumor segmentation with better accuracy. So that entire society will be benefited, Clinical expert will get a second opinion and they can properly plan the treatment.

4. Objectives

The objectives are to study the above-discussed problem and to provide the engineering solution to the problem.

For solving the problem, we will work in the direction summarized as follows-

- To study different image segmentation algorithms
- To design an algorithm for automatic liver segmentation
- To design an algorithm for automatic segmentation of liver and liver tumor
- To localize the tumor in the liver region and Calculate the tumor burden for treatment planning
- To analyze the performance of algorithms with different liver datasets available publically
- To analyze the algorithms using statistical performance measures commonly utilized in liver-related segmentation methods
- To compare the performance with previously developed algorithms

5. Methodology

The Methodology which will be adopted to segment liver and the liver tumor is as shown in fig. 5.

- The first step is input database collection of liver and liver tumor images required for processing using algorithm designed.
- The input image database is required pre-processing like cropping, artefacts removal, data augmentation, and noise removal.
- Apply the designed algorithm on the pre-processed database to segment liver and liver tumor.
- Once the segmentation result obtained it can be evaluated using different statistical performance measures commonly utilized in liver-related segmentation.

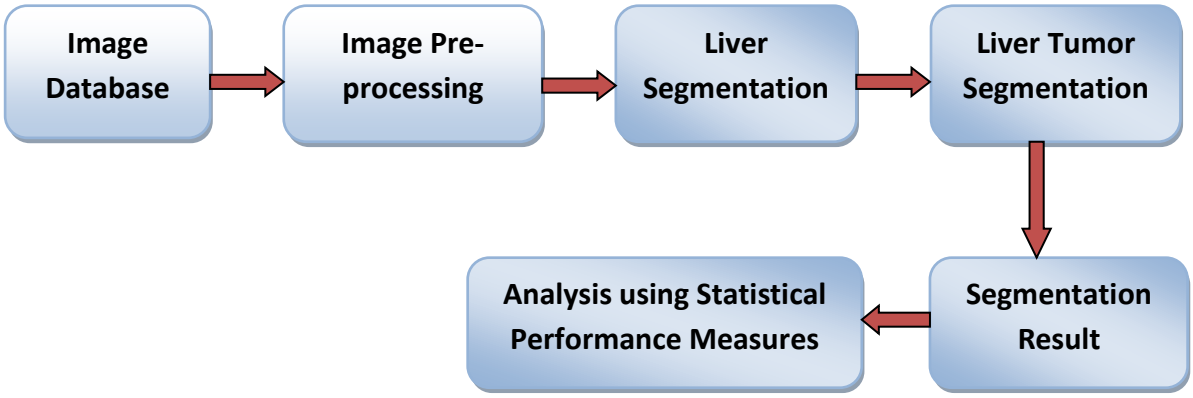

Fig.5 Proposed liver and liver tumor segmentation methodology

6. Importance of study/ Society application

6.1 International Status

Recently the Artificial Intelligence (AI) and Machine Learning (ML) have progressed rapidly for Medical image analysis to automate the diagnosis process however, traditional machine learning methods are not sufficient to deal with a complex problem. The high-performance computing with machine learning, promise the capacity to deal with big medical image data for accurate and efficient diagnosis. Deep learning is the approach for medical image analysis with very high accuracy. Deep learning will not only help to select and extract features but also construct new ones, furthermore, it does not only diagnose the disease but also measure predictive target and provides actionable prediction models to help physicians efficiently[4].

Bilic, Patrick, et al. [11] reported the set-up and results of the Liver Tumor Segmentation Benchmark (LiTS) organized in conjunction with the IEEE International Symposium on Biomedical Imaging (ISBI) 2017 and International Conference on Medical Image Computing & Computer-Assisted Intervention (MICCAI) 2017. In this paper, they discussed detail literature review of the previous algorithms developed in the literature to segment liver and liver tumor. The results obtained by the deep learning-based state-of-art methods proposed and how training data is important to get a good result in deep learning algorithms. The methods presented have shown good results on the malignant tumor segmentation but segmentation of small lession remains a challenging task. By providing a large amount of data to the deep learning methods it is possible to enhance the accuracy of segmentation.

Romero, Francisco Perdigon, et al. [22] Introduce an end-to-end deep learning approach to assist in the discrimination between liver metastases from colorectal cancer and benign cysts in abdominal CT images of the liver. The approach incorporates the efficient feature extraction of InceptionV3 combined with residual connections and pre-trained weights from ImageNet. The architecture also includes fully connected classification layers to generate a probabilistic output of lesion type.

Ahmad, Mubashir, et al. [6] proposed an automatic feature learning algorithm based on the deep belief network (DBN) for liver segmentation. The proposed method was based on training by a DBN for unsupervised pre-training and supervised fine-tuning. The whole method of pre-training and fine-tuning is known as DBN-DNN. Instead of training pixel-by-pixel here block training used to identify the liver, to saves memory and computational time. An automatic active contour method is applied to refine the results in post-processing.

6.2 National Status

Das, Amita, et al. [19] proposed an automated watershed-Gaussian based deep learning (WGDL) technique for effective delineate (trace) the cancer lesion in computed tomography (CT) images of the liver to detect and identify three different types of liver cancer (HEM, HCC, MET) in CT images. In this technique, the liver was separated using marker controlled watershed segmentation process and finally cancer affected lesion was segmented using the Gaussian mixture model (GMM) algorithm. After tumor segmentation, various statistical, geometrical and texture features were extracted from the segmented images using gray level co-occurrence matrix (GLCM) method and used for the classification. These segmented features were fed to deep neural network (DNN) classifier for automated classification of three types of liver cancer i.e. hemangioma (HEM), hepatocellular carcinoma (HCC) and metastatic carcinoma (MET).

Kumar, S. S. et.al [20] proposed an approach for the automatic segmentation of liver and tumor from CT images mainly used for Computer-aided diagnosis of the liver is proposed. The method uses region growing, facilitated by pre and post-processing functions for the automatic segmentation of the liver and Alternative Fuzzy C-Means (AFCM) algorithm for tumor segmentation. For pre-processing of images prior knowledge is used to detect useful regions from the images. Region growing segmentation methods using seed point used to and after that post-processing is done using morphological operations. The tumor segmentation from the segmented liver is done using the Alternative FCM clustering.

Biswas, Ankur et.al. [21] Proposed Two geometric contours using level set method were initialized and cascaded for a combined segmentation of the liver and its lesions. In the first step, a contour to segment the liver was initialized that served as the volume of Interest (VOI) input for a second geometric contour. The second contour exclusively segmented lesions within the predicted liver VOIs of the first step. The proposed method was assessed on the MIDAS dataset and showed to be capable of delineating single as well as multiple tumors of any dimension even in case of low contrast or weak boundaries of tumors.

6.3 Significance of the study

The less availability of treatment planning for liver and liver cancer it is very difficult to diagnose and plan liver-related complications.

The WHO report shows that the death rate and other statistics of liver cancer. Diagnosis of liver cancer at the earlier stage is very important to avoid further complication and plan the treatment.

By developing automatic Computerised aided diagnosis of liver cancer will reduce the human errors in the manual segmentation and improve the accuracy of segmentation as well as reduce the time required. Also, it helps to Radiologist to segment the correct region of interest and provide the second opinion for the radiologist. It became ease for oncologists to plan for better treatment. It will reduce the death rate of liver cancer by detecting it at the early stage and providing details to the experts for better planning of treatment.

This automatic CAD liver cancer segmentation will greatly impact on the society and healthcare sector.

7. Proposed work Plan

Year 1 (2019-20)	• Course work completion • Literature Survey of Liver and Liver Tumor Segmentation • Research Background Development and Research Tools understanding • Implementation of Existing Methodologies
Year 2 (2020-21)	• Working on Formulation of Methodology for Liver and Liver tumor segmentation • Implementation of new methodology • Result Analysis and Comparison with previous Methods • Research Article Writing • Submission of research Article in Journals
Year 3 (2021-22)	• Synopsys Submission • Thesis Writing • Thesis Submission

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